Finding Nemo

Harsh Mehta Rohitashwa Chakraborty Karthick Ramasubramanian

Executive Summary

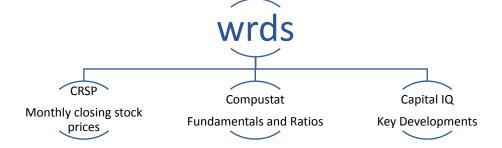
Using industry fundamental data, text data from news articles, our team has attempted to predict the direction of change of Net Income using Machine Learning.

We would use the results to build quarterly balanced portfolios and test it against Market and Fama French 3 factor Portfolios.

Objective

- Forecast the direction change in Net Income
- Without Normalizing using
 Shares Outstanding or Revenue
 we believe the data would be
 less granular and hence more
 accurate thereby granting our
 model more predictive power
- Our final objective is to build portfolios with statistically significant Alphas

Data Sources



- We are using data starting from 2001 to 2020
- The fundamental company data has been obtained from Compustat.
- The News data obtained from Capital IQ (Compustat) includes:
 - Category of the Article Sales, Acquisitions, Stock Splits etc...
 - The header
 - A brief description of the news article
- Stock prices were pulled from CRSP
- Market Data and the Fama French 3 factor model data has been obtained from Kenneth R French Data Library

Approach

Data Preprocessing

- Exploratory Data Analysis
- Dropping rows and columns with missing values
- Preparing target variable

Feature Engineering

- Adding % change columns
- Cleaning the unstructured data in the key events file.
- Mapping event headlines and implementing sentiment analysis on the cleaned vectorized data from key events.

Model Building

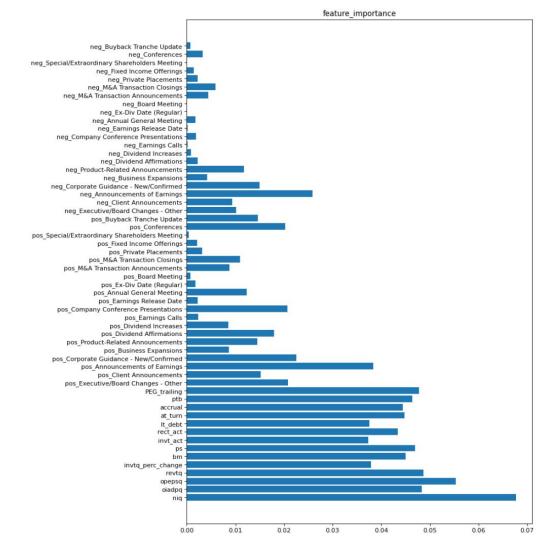
- Univariate logistic regressions to find significant variables
- Multivariate logistic regression on subset of variables
- Train on previous 4 quarters and predict change in direction in NI for next quarter

Portfolio Construction

- Equal Weighted portfolios
- Different probability cutoffs considered
- Rebalanced quarterly
- Regressed returns against fama-French 3 factor model

Variables Used

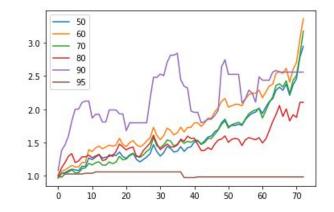
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dir', 'public date', 'niq', 'oiadpq', 'opepsq', 'revtq',
 invtq perc change', 'bm', 'ps', 'invt act', 'rect act', 'lt debt',
 at turn', 'accrual', 'ptb', 'PEG trailing',
  pos Executive/Board Changes - Other', 'pos Client Announcements',
 'pos Announcements of Earnings',
 'pos Corporate Guidance - New/Confirmed', 'pos Business Expansions',
 'pos Product-Related Announcements', 'pos Dividend Affirmations',
 'pos_Dividend Increases', 'pos_Earnings Calls',
 'pos Company Conference Presentations', 'pos Earnings Release Date',
 'pos Annual General Meeting', 'pos Ex-Div Date (Regular)',
 'pos Board Meeting', 'pos M&A Transaction Announcements',
 'pos M&A Transaction Closings', 'pos Private Placements',
 'pos Fixed Income Offerings',
 'pos Special/Extraordinary Shareholders Meeting', 'pos Conferences'.
 'pos Buyback Tranche Update', 'neg Executive/Board Changes - Other',
 'neg Client Announcements', 'neg Announcements of Earnings',
 'neg Corporate Guidance - New/Confirmed', 'neg_Business Expansions',
 'neg Product-Related Announcements', 'neg Dividend Affirmations',
 'neg Dividend Increases', 'neg Earnings Calls',
 'neg Company Conference Presentations', 'neg Earnings Release Date',
 'neg Annual General Meeting', 'neg Ex-Div Date (Regular)',
 'neg Board Meeting', 'neg M&A Transaction Announcements',
 'neg M&A Transaction Closings', 'neg Private Placements',
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 'neg Buyback Tranche Update'],
dtype='object')
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AUC = 0.67

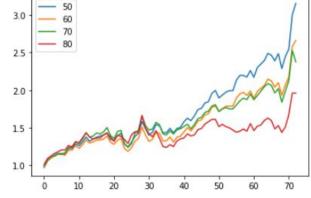
Only Structured Data





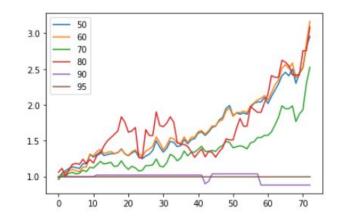
	coef	std err	t	P> t	[0.025	0.975]
const	0.0173	0.007	2.432	0.018	0.003	0.032
Mkt-RF	-0.0009	0.002	-0.601	0.550	-0.004	0.002
SMB	0.0027	0.003	1.026	0.308	-0.003	0.008
HML	-0.0025	0.002	-1.249	0.216	-0.007	0.002
RF	-0.0090	0.043	-0.210	0.835	-0.095	0.077



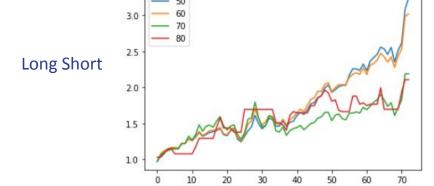


	coef	std err	t	P> t	[0.025	0.975]
const	0.0156	0.007	2.123	0.037	0.001	0.030
Mkt-RF	0.0001	0.002	0.070	0.944	-0.003	0.003
SMB	0.0032	0.003	1.190	0.238	-0.002	0.009
HML	-0.0035	0.002	-1.655	0.103	-0.008	0.001
RF	-0.0315	0.044	-0.709	0.481	-0.120	0.057

Structured and Unstructured Data



	coef	std err	t	P> t	[0.025	0.975]
const	0.0175	0.007	2.406	0.019	0.003	0.032
Mkt-RF	0.0004	0.002	0.288	0.774	-0.003	0.003
SMB	0.0024	0.003	0.880	0.382	-0.003	0.008
HML	-0.0014	0.002	-0.695	0.489	-0.006	0.003
RF	-0.0224	0.044	-0.510	0.612	-0.110	0.065



Long Only

	coef	std err	t	P> t	[0.025	0.975]
const	0.0168	0.007	2.246	0.028	0.002	0.032
Mkt-RF	0.0003	0.002	0.180	0.858	-0.003	0.003
SMB	0.0032	0.003	1.149	0.255	-0.002	0.009
HML	-0.0031	0.002	-1.459	0.149	-0.007	0.001
RF	-0.0263	0.045	-0.581	0.563	-0.117	0.064

Trying different transformations of the features(log) and adding lags

Implementing NN and SVM and find a good balance between model complexity and explainability

Next Steps

Analyzing richer unstructured data like Earnings Call Transcripts

Fitting a ARIMA model to understand the predictive power of lagged effects

References

OU, Jane A, and Stephen H Penman. "Improving Earnings Predictions and Abnormal Returns with Machine Learning." https://www.sciencedirect.com/Science/Article/Abs/Pii/0165410189900177, Nov. 1989,

Hunt, Joshua. "Improving Earnings Predictions with Machine Learning Hunt ..." Improving Earnings Prediction, 10/2019/12, https://zicklin.baruch.cuny.edu/wpcontent/uploads/sites/10/2019/12/Improving-Earnings-Predictions-with-MachineLearning-Hunt-Myers-Myers.pdf.